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Does noncompliance with COVID-19 regulations impact the depressive symptoms of others?☆

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ABSTRACT

Before vaccines became commonly available, compliance with nonpharmaceutical only preventive measures offered protection against COVID-19 infection. Compliance is therefore expected to have physical health implications for the individual and others. Moreover, in the context of the highly contagious coronavirus, perceived noncompliance can increase the subjective risk assessment of contracting the virus and, as a result, increase psychological distress. However, the implications of (public) noncompliance on the psychological health of others have not been sufficiently explored in the literature. Examining this is of utmost importance in light of the pandemic's elevated prevalence of depressive symptoms across countries. Using nationally representative data from South Africa, we explore the relationship between depressive symptoms and perceived noncompliance. We examine this relationship using a double machine learning approach while controlling for observable selection. Our result shows that the perception that neighbors are noncompliant is correlated with self-reported depressive symptoms. Therefore, in the context of a highly infectious virus, noncompliance has detrimental effects on the wellbeing of others.

1. Introduction

Several papers have argued that the COVID-19 pandemic has increased the population's psychological distress. It has become apparent that the COVID-19 health cost includes not only physical but also mental health (Adams-Prassl et al., 2022; Oyenubi and Kollamparambil, 2022; Posel et al., 2021; Vindegaard and Benros, 2020; Xiong et al., 2020). The findings imply that apart from those directly affected by the pandemic (e.g., COVID-19 patients and health workers), the pandemic and associated restrictions have a negative effect on the general population's mental health. The additional mental stress caused by the pandemic can manifest itself in various ways because factors influencing psychological wellbeing can be internal to the individual, such as genetics, disposition, and developmental history, or external, such as circumstances and environment (Allen et al., 2014; Compton and Shim, 2015; Ellis and Boyce, 2011; Keyes et al., 2010; Ungar and Theron, 2020).

Channels that have been documented in the literature (in the context of COVID-19) include job loss and financial concerns (Oyenubi and Kollamparambil, 2022; Posel et al., 2021), social isolation brought about by the lockdown and social distancing protocols (McQuaid et al., 2021; Palgi et al., 2020; Wang et al., 2017) and heightened risk perception (Kim et al., 2020; Oyenubi et al., 2022; Oyenubi and Kollamparambil, 2020). It has also been demonstrated that (own) noncompliance with COVID-19 regulation is linked to (own) depressive symptoms (Byun et al., 2022). However, there is another channel that has not been explored in the literature: the behavior of neighbors in terms of compliance with nonpharmaceutical measures. This is especially important in the context of the lockdown measures intended to halt the spread of the highly infectious virus, where one's protection is dependent not only on one's own actions but also on the compliance of others with whom one interacts.

We note that the literature on compliance with COVID-19 regulations has primarily focused on predictors of compliance, with this strand of the literature demonstrating that age, political orientation/trust in government, perceived vulnerability, gender, and other factors explain compliance (Blayac et al., 2022; Lin et al., 2021; Min et al., 2020; Mohanty and Sharma, 2022; Wright and Fancourt, 2021). However, the

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impact of noncompliance on the psychological health of those who witness this behavior has not been explored. This is significant because the discovery that compliance varies by demographic characteristics under strict lockdown conditions (i.e., earlier in the pandemic) implies that one can share space with a noncompliant person. This paper contributes to the literature on health regulation compliance and its implications by focusing on the relationship between perceived noncompliance and others' psychological wellbeing. This is important for informing policy debate on compliance, both in the context of the ongoing COVID-19 pandemic and in the context of future pandemics (it has been noted that a pandemic of similar impact to COVID-19 has a 2% probability of occurring in any given year, and this probability accumulates over time (Marani et al., 2021)).[1]

Because COVID-19 risk perception is correlated with depressive symptoms (Kim et al., 2020), noncompliance by neighbors can influence risk perception and thus harm depressive symptoms. The mechanism is as follows: consider the physical environment with which an individual interacts as a common/shared resource. This resource includes shopping malls, hospitals, and other workspaces that remained open despite the restrictions because they were deemed essential services. While lockdown restrictions reduce interaction with the general population, these neighborhood resources still serve as a shared space for the virus to spread. Therefore, in the absence of vaccination (during the early stages of the pandemic), infection control relies heavily on collective compliance with nonpharmaceutical interventions within one's social environment. Given the relative lack of knowledge about COVID-19 in the initial phases of the pandemic, a perception that one's neighbors are not following COVID-19 preventive measures may increase the risk of contracting and transmitting the virus through shared spaces.

Because of the virus's highly infectious nature, health concerns associated with COVID-19 can be worrisome. Information about how the virus is transmitted suggests that COVID-19 is spread via droplets emitted by breathing, talking, coughing, and sneezing[2] and may also be airborne.[3] This raises concerns about breathing the same air or interacting with surfaces that have been contaminated by previous users (Shen and Bar-Yam, 2020). Preventive measures advocated by the World Health Organization include washing hands, disinfecting surfaces, and avoiding touching one's face. This is significant because the COVID-19 virus has been shown to live for several hours in the air and for up to six days on surfaces (Chin et al., 2020; Dong, 2003; Kampf et al., 2020; Rabenau et al., 2005; Van Doremalen et al., 2020; Warnes et al., 2015),[4] which increases the risk of transmission by fomites (inanimate surface or objects).

However, avoiding touching one's face (or even surfaces) is difficult; a pre-COVID-19 study found that medical students (who are trained and expected to be more aware) touch their eyes, nose, and mouth more than 20 times an hour (Kwok et al., 2015), which is not significantly different from what is observed in the general population (Christensen et al., 2020). Some authors suggest that such movements occur with little or no awareness (Mueller et al., 2019), emphasizing the difficulty in implementing the recommendation that people keep their hands away from their faces to reduce their chances of contracting COVID-19. There is also evidence that stress increases the desire to touch one's face (Grunwald et al., 2014), implying that an increase in stress levels during the pandemic (due to financial concerns, for example) may increase spontaneous facial self-touch gestures.

The implication is that people may unintentionally engage in facial self-touch gestures at the start of the pandemic. When combined with the perception that one's neighbors with whom one shares public spaces are not adhering to preventive measures, this may heighten risk perception. Our main hypothesis is that a perception that neighbors are not following COVID-19 protocols may increase the incidence of depressive symptoms, which is mediated by an increased risk perception of infection. We contend that shared spaces are a plausible mechanism for this. This is because touching surfaces and then one's face can happen involuntarily because such behavioral changes can take time. Therefore, sharing space with neighbors who are perceived to be breaking prevention rules may increase the risk of contracting the virus. We note that non-adherence by neighbors does not have to be an objective truth for the positive relationship between perceived non-adherence and depressive symptoms to hold (Khan et al., 2020); that is, a subjective perception will suffice.

We found evidence of a negative externality associated with perceived noncompliance in terms of self-reported depressive symptoms. Using the multivalued treatment approach, we model the relationship between depressive symptoms and neighborhood behavior (Cattaneo, 2010). The double machine learning (DML) model (Knaus, 2021) is used to control for selection on observables in the multivalued treatment framework (Rosenbaum and Rubin, 1983) (i.e., achieve balance in the distribution of covariates). Furthermore, using the approach of Oster (2019), we show that at the inception of the pandemic, the result is robust to unobserved factors (or the violation of the selection on observables assumption). Specifically, those who believe their neighbors have a higher level of non-adherence are more likely to report depressive symptoms (this is measured by the perceived intensity of noncompliance, i.e., the number of neighbors one believes are going out to drink alcohol in violation of COVID-19 restrictions) between July and August 2020 (Wave 2 of our data). The relationship between a perception that neighbors are not wearing masks and depressive symptoms is similar, albeit weaker, for data collected between November and December 2020 (Wave 3). Furthermore, the mask-wearing result is not robust to unobserved factors. This could be attributed to the difference in the types of perceived violations or to the fact that experience with and knowledge of COVID-19 has grown in the second period (e.g., as noted in footnote 3, there has been some rebuttal to the finding that the virus can remain active on a surface for up to 6 days).

Given the foregoing, understanding the pandemic's mental health impact is especially important for South Africa, which has higher rates of mental health disorders than other countries (Herman et al., 2009). Despite the high incidence of mental health disorders, access to mental healthcare in the country is severely limited (Hickson and Kriegler, 1991). It is also worth noting that identifying the link between collective compliance (or good health behavior) and mental health during the pandemic emphasizes the role of compliance as a public good. Therefore, the argument for enforcement in the public interest becomes stronger. This type of relationship could also be extended to the context of vaccine hesitancy. However, we note that the case of vaccine hesitancy is different since noncompliance cannot be easily observed. Therefore, the argument in favor of a vaccine mandate for public health benefit (mental and physical) becomes stronger on the grounds that it protects the health of others (Anomaly, 2011).

Our results also contribute to the literature on negative externalities in infectious diseases (Diekmann, 2022; Leeson and Rouanet, 2021). In this context, negative externality refers to the cost that a person's health behavior imposes on others that is not accounted for by the person exhibiting the behavior (Leeson and Rouanet, 2021). From this perspective, compliance is a public good, and noncompliance, increases the risk of infection for others. The fundamental issue here is that the

[1] As noted by Marani et al. (2021), the implication is that someone born in year 2000 would have about a 38% chance of experiencing such pandemic by now.

[2] WHO https://www.who.int/health-topics/coronavirus#tab=tab_1.

[3] See https://www.who.int/news-room/commentaries/detail/modes-of-transmission-of-virus-causing-covid-19-implications-for-ipc-precaution-recommendations.

[4] Others argue that the experiments performed by these studies do not fit scenarios that may occur in real-life situations in terms of the concentration particles of infectious virus (Goldman, 2020). Goldman (2020) argued that although infected surfaces are a risk factor, the virus is not likely to be active on such surfaces for more than a couple of hours.

decision to take preventive measures imposes a cost to individuals (a cost that has financial and convenience components). Therefore, the adoption of such measures may be influenced by perceived susceptibility. Individuals who do not have pre-conditions that increase the risk of serious illness or death due to COVID, for example, may be less likely to take preventive measures because the cost may outweigh the benefit. However, noncompliance imposes an additional cost on others, not only through increased infection risk, but also through negative implications for mental wellbeing. Our main argument is that the social benefit outweighs the private cost of compliance, emphasizing the importance of ensuring better compliance through increased awareness and pecuniary penalties for noncompliance.

2. Background on the pandemic and lockdown in South Africa

The South African minister of health confirmed the first COVID-19 virus infection in South Africa on March 5, 2020. Following this development, the President declared a State of National Disaster on March 15, and measures such as travel restrictions and school closures were implemented immediately. On March 26, 2020, South Africa went into total lockdown. Although necessary to slow virus transmission, this pandemic response has been argued to have negative consequences for mental health (Oyenubi and Kollamparambil, 2020). South Africa went into lockdown using a five-level alert system, with higher levels indicating more stringent conditions. The restrictions are implemented based on the number of COVID-19 infections and the preparedness of health facilities to handle the disease burden (Government Gazette, 2020). Beginning March 26, the government gradually reduced the level of lockdown restrictions to allow the economy to resume normal operations. Apart from this initial shock, the country changed the severity of lockdown restrictions seven times during the period covered by our data.[5]

The implication of the hard (level 5) lockdown is that economic activities are grounded to a halt. One implication of this is the losses of jobs and income in the country (Casale and Posel, 2020; Jain et al., 2020). According to estimates, between 2.2 and 2.8 million jobs were lost in South Africa between February and April 2020. This has resulted in increased financial concerns, which can harm psychological health (Posel et al., 2021). Furthermore, Nwosu and Oyenubi (2021) reported that in this period, self-reported poor health became more concentrated among the poor compared to 2017. This is significant because research has shown that higher psychological wellbeing is related to higher self-rated health (Kaleta et al., 2009).

Enforcement of the lockdown restrictions was not universally successful in South Africa. For example, some newspaper reports suggest that life continued as normal in some parts of the country despite the lockdown.[6] Furthermore, after only seven days of the lockdown, the South African Police Service arrested a total of 2289 people for violating lockdown rules.[7] The implication here is that these restrictions were violated in some places. Although these dynamics are not dissimilar to what occurred in other African countries (and elsewhere), our main point is that such violations may contribute to mental health burden through risk perception. Based on the same data we use for our analysis, Kollamparambil and Oyenubi (2020) report that subjective risk perception of COVID-19 infection increased by 17% between April and June 2020. Similar dynamics have been observed in other locations. Our main hypothesis is that apart from the financial channel, environmental factors such as neighbor behavior may contribute to the rise in reports of psychological distress.

3. Data and methodology

3.1. Data and variables

Our analysis relies on data from waves 2 and 3 of the National Income Dynamic Study-Coronavirus Rapid Mobile Survey (NIDS-CRAM). The NIDS-CRAM is a special follow-up with a subsample of adults from households in a nationally representative survey (NIDS Wave 5). NIDS-CRAM is a much shorter questionnaire than the core NIDS panel study, with a focus on the COVID-19 pandemic and the national lockdown (Ingle et al., 2020). Wave 2 of NIDS-CRAM was conducted between July 13, 2020, and August 13, 2020, and wave 3 was conducted between November 2, 2020, and December 13, 2020. The availability of questions covering the perception of neighborhood adherence led to the selection of these two waves (out of a total of five). Furthermore, because the relationship between neighborhood behavior and depressive symptoms is expected to be stronger earlier in the pandemic, we limit the analysis to NIDS-CRAM waves 2 and 3. This is due to the rapid evolution of knowledge and information about the coronavirus during this period, which will have implications for individual risk perception and behavior. Lastly, information about depressive symptoms is not included in wave 1 of the data.

The outcome variable is depressive symptoms, which are measured using the two-question version of the Patient Health Questionnaire (PHQ-2).[8] The two questions administered to derive the PHQ-2 dummy are: "*Over the last 2 weeks, have you had little interest or pleasure in doing things?*" and "*Over the last 2 weeks, have you been feeling down, depressed, or hopeless.*" Both questions could be responded to as "*not at all*," "*several days*," "*more than half the days*" or "*nearly every day*." The responses are coded from 0 to 3, so adding the codes from the two questions yields the PHQ-2 scale, which has a range of 0–6. As the values increase, so do the levels of depressive symptoms. In modeling the outcome variable, we follow the findings of a recent study (Manea et al., 2016) that PHQ-2 has low sensitivity at the recommended cut-off of PHQ-2 ≥ 3 (Kroenke et al., 2003) and a cut-off of PHQ-2 ≥ 2 may be preferable, particularly in cases where the prevalence of depression is high. The COVID-19 context and the study's location in South Africa can be argued to fit the description of a situation with a high prevalence of depression. Individuals who score above this level are said to screen positive for depression.

Our main independent variable (or treatment) captures the respondent's perception of the behavior of their neighbors. Waves 2 and 3 used different questions to collect information on neighborhood compliance. In wave 2, our multivalued treatment is based on the answer to the question "*How many people in your neighborhood, if any, went out and drank alcohol with friends during lockdown?*" Hereafter we refer to this as "violation of alcohol restriction." The options given for response are "*None*," "*A few people*," "*About half of the people*," and "*Most people.*" For wave 3, it is based on the answer to the question "*How many people in your area wear mask in public?*" The options for response are "*Everyone*," "*Most people*," "*About half of the people*," "*A few people*," and "*No one wear mask.*" Hereafter we refer to this as "compliance with mask mandate". We hypothesize that because these responses gradually reflect a higher level of noncompliance, a higher level of noncompliance will translate into a higher likelihood of reporting depressive symptoms (net of the influence of other observed factors).

The survey also included a variety of questions about the respondents' demographic and socioeconomic characteristics. Many of

[5] See https://www.gov.za/covid-19/about/about-alert-system.

[6] See https://www.timeslive.co.za/news/south-africa/2020-04-06-lockdown-life-continues-as-normal-in-some-parts-of-the-eastern-cape/, https://businesstech.co.za/news/government/400503/concern-that-townships-are-not-following-south-africas-lockdown-regulations/, and https://www.enca.com/news/sa-lockdown-spotlight-compliance-govt-regulations-suburban-areas.

[7] See https://www.news24.com/news24/SouthAfrica/News/dont-give-us-a-reason-to-arrest-you-cele-as-lockdown-arrests-rise-to-2-289-20200403.

[8] PHQ-2 is the abbreviated version of the widely used PHQ-9 (Kroenke et al., 2003). It has been validated as a reliable screening method for depressive symptoms in South Africa (Baron et al., 2017)

these are used as control variables to investigate the relationship between perceived non-adherence and depressive symptoms. The included controls are COVID-19 risk perception (derived from the question "*Do you think you are likely to get the coronavirus?*") (this variable is also used as a mediator of the relationship of interest when we discuss plausible mechanisms); a measure of self-efficacy (i.e., dummy variable that is 1 if respondents believe that positive health outcomes can be achieved through personal action and 0 otherwise); household hunger; household income per capita (not included in wave 3 data); grant receipt; dummy variable that is 1 if household lost income within the last 4 weeks; geo-location (traditional/Chiefdom, informal dwelling, township, formal residence, farm, and smallholding); age; the square of age; gender; race (African dummy variable); marital/partner status; dwelling type (flat, traditional house or hut, informal dwelling or shack, and other dwellings); employment status; years of schooling; and number of preventive measures adopted by the respondent.

Finally, we consider the direct effect of the pandemic's progression on mental health. In other words, the pandemic can increase an individual's report of depressive symptoms regardless of neighborhood compliance with COVID-19 regulations. We control for COVID-19 reproductive rate on the day respondents were interviewed to capture this effect (this is used as a proxy to capture the direct relationship between being in a pandemic and reporting depressive symptoms). This variable is derived from the database "our world in data" (Ritchie et al., 2020). COVID-19 reproductive rate is a daily estimate at the national level of the average number of new infections caused by a single infected individual (note that this information is merged with the survey data by date of respondent interview). Controlling for COVID-19 reproductive rate allows our analysis to exploit variation in this variable over time, as respondents were interviewed over one month in each wave.

In terms of the rationale for covariate selection, we control for covariates that may be associated with perceptions of neighborly behavior and depressive symptoms (Oyenubi, 2020). For example, a recent study found that race, education, area type, and risk perception are correlated with an individual's perception of community members' adherence to COVID-19 lockdown rules (Dukhi et al., 2021). In the context of the COVID-19 pandemic in South Africa, additional factors such as household hunger, age, gender, having a partner, and employment status are found to be associated with depressive symptoms (Kim et al., 2020; Oyenubi and Kollamparambil, 2020; Posel et al., 2021). Tables 1A and 1B shows the summary statistics for waves 2 and 3 of our dataset.

Table 1A
Summary statistics (Wave 2).

Statistic	N	Mean	St. Dev.	Min	Max
Outcome variable					
PHQ-2 raw	3246	1.28	1.61	0	6
PHQ-2 (cut-off ≥2)	3246	0.37	0.48	0	1
Key variable of interest: Number of people in Violation of Alcohol restriction[a]					
No one	3246	0.29	0.45	0	1
A few people	3246	0.32	0.47	0	1
About half of the people	3246	0.09	0.29	0	1
Most people	3246	0.29	0.46	0	1
Other controls					
Able to avoid COVID	3246	0.84	0.36	0	1
Risk perception[b]	3246	0.44	0.50	0	1
Household hunger	3246	0.18	0.39	0	1
HH income per capita	3246	6.40	1.30	0.00	11.65
Receive govt grant	3246	0.78	0.41	0	1
Household lost income	3246	0.16	0.36	0	1
Traditional (Area)	3246	0.26	0.44	0	1
Informal settlement (Area)	3246	0.04	0.19	0	1
Township (Area)	3246	0.32	0.47	0	1
Formal (Area)	3246	0.23	0.42	0	1
Farm (Area)	3246	0.11	0.32	0	1
Small holding (Area)	3246	0.03	0.18	0	1
age	3246	40.47	15.37	18	102
age squared	3246	1873.66	1459.60	324	10,404
male	3246	0.35	0.48	0	1
African	3246	0.86	0.35	0	1
Has partner	3246	0.34	0.47	0	1
Flat (Dwelling)	3246	0.73	0.44	0	1
Traditional (Dwelling)	3246	0.14	0.35	0	1
Informal (Dwelling)	3246	0.10	0.30	0	1
Other (Dwelling)	3246	0.03	0.17	0	1
Employed	3246	0.43	0.49	0	1
Years of schooling	3246	10.67	3.99	0	16
Years of schooling squared	3246	1.30	0.76	0.00	2.56
No of preventive measures	3246	2.59	1.07	0	8
COVID-19 reproduction rate	3246	0.96	0.12	0.73	1.22

[a] *How many people in your neighborhood, if any, went out and drank alcohol with friends during lockdown?*.
[b] This variable is also used as the mediating variable.

3.2. Methodology

Our estimation can be interpreted as the impact of the perception of neighbor's compliance to COVID-19 rules on depressive symptoms under the selection on observables assumption. This assumption implies that the variables controlled for in the analysis are sufficient to render the outcome (depressive symptoms) independent of treatment assignment. We use the DML approach (Bodory et al., 2022; Chernozhukov et al., 2018; Knaus, 2021, 2022) to obtain weights that balance the distribution of covariates across the multivalued treatment levels under this assumption. DML is a causal machine learning technique that allows for counterfactual prediction and inference under the assumption of ignorability. Causal machine learning techniques have been shown to improve causal analysis in observational studies (Farrell, 2015; Knaus, 2021).

The approach has an advantage over alternatives that do not leverage machine learning techniques.[9] Specifically, machine learning allows for greater flexibility in propensity score specification, as these methods easily accommodate higher-order and interaction terms in propensity score specification. While including these terms strengthens the ignorability assumption, it also increases the number of covariates (i.e., sparse model). The DML method handles the resulting variable selection problem while maintaining uniformly valid statistical inference (Chernozhukov et al., 2018). Apart from that, DML supports the use of balancing checks (for example using the standardized difference in means). As noted by Knaus (2021), balancing checks are arguably more important in the case of sparse models because it is important to ensure that the result is not being driven by covariates that were not selected during the variable selection stage. Finally, DML supports sensitivity analysis, which is critical in a machine learning approach because the resulting estimate may be affected by the choice of turning parameters (which controls model complexity). Therefore, it is critical to assess the sensitivity of the result to these parameters (Knaus, 2021).

We assume that t is a given level of treatment from a random set $D \in \mathscr{T}$ where $t_i, i = 1\ldots d$ are the different levels of treatment. Each $i = 1\ldots n$ has potential outcome Y_i^t for each value of treatment $d_i = t$.However, only one value of the potential outcomes (i.e., the realized outcome) is observed for each individual. The observed outcome can be written as $Y_i = \sum_{t=0}^{t} 1\{D_i = t\} Y_i^t$, and the potential outcomes $T_i \neq t$ are unobserved. Specifically, the levels of treatment or group status correspond to the different levels of neighbors' non-adherence as perceived by the individual in group t (i.e., "*None*," "*A few people*," "*About half of the people*," and "*Most people*" in the case of wave 2). We are interested in the average potential outcomes (APO) $\mu_t = E[Y_i^t]$ and their differences. Because this is a multivalued treatment setting, we are interested in possible pairwise comparisons, such as $\mu_m - \mu_n = E[Y_i^m - Y_i^n]$ for $m \neq n$. Here we focus on the average treatment effect (ATE) following Knaus (2021). We posit that a perception that more neighbors are not adhering

[9] For example, covariate balancing propensity scores (Imai and Ratkovic, 2014) and entropy balancing (Hainmueller, 2012).

Table 1B
Summary statistics (Wave 3).

Statistic	N	Mean	St. Dev.	Min	Max
Outcome variable					
PHQ-2 raw	5002	1.53	1.70	0	6
PHQ-2 (cut-off ≥2)	5002	0.43	0.50	0	1
Key variable of interest: Compliance with mask mandate[a]					
Everyone wear mask	5002	0.16	0.37	0	1
Most people wear mask	5002	0.36	0.48	0	1
Half of the people wear mask	5002	0.15	0.36	0	1
Few people wear mask	5002	0.29	0.45	0	1
No one wears mask	5002	0.03	0.18	0	1
Other controls					
Able to avoid COVID	5002	0.87	0.34	0	1
Risk perception[b]	5002	0.36	0.48	0	1
Household hunger	5002	0.21	0.41	0	1
Receive Govt grant	5002	0.78	0.41	0	1
Household lost income	5002	0.41	0.49	0	1
Traditional (Area)	5002	0.28	0.45	0	1
Informal settlement (Area)	5002	0.04	0.19	0	1
Township (Area)	5002	0.34	0.47	0	1
Formal (Area)	5002	0.22	0.41	0	1
Farm (Area)	5002	0.09	0.29	0	1
Small holding (Area)	5002	0.03	0.18	0	1
age	5002	40.77	15.58	18	100
age squared	5002	1904.69	1472.40	324	10,000
male	5002	0.37	0.48	0	1
African	5002	0.86	0.34	0	1
Has partner	5002	0.34	0.47	0	1
Flat (Dwelling)	5002	0.77	0.42	0	1
Traditional (Dwelling)	5002	0.12	0.32	0	1
Informal (Dwelling)	5002	0.09	0.29	0	1
Other (Dwelling)	5002	0.02	0.14	0	1
Employed	5002	0.48	0.50	0	1
Years of schooling	5002	10.73	4.09	0	22
Years of schooling squared	5002	1.32	0.80	0	5
No of preventive measures	5002	2.61	1.00	0	8
COVID-19 reproduction rate	5200	1.24	0.11	0.98	1.47

[a] "*How many people in your area wear mask in public?*"
[b] This variable is also used as the mediating variable.

corresponds to a higher probability of screening positive for depressive symptoms.

Due to selection $\mu_t \neq E[Y_i^t]$, however, μ_t can be identified if we assume that (i) treatment status is as good as random conditional on the observed covariates X_i (2) each unit has a nonzero probability of being observed in each treatment category. These assumptions are summed up as the strong ignorability assumption (Rosenbaum and Rubin, 1983). DML is based on the doubly robust score, as opposed to approaches that rely on outcome or treatment regression. Even if one of the outcomes or treatment regressions is misspecified, the doubly robust estimator is known to remain consistent (Glynn and Quinn, 2010; Zhao and Percival, 2017). Therefore the "double" in DML emphasizes that the estimator is not based on a single equation, whereas "machine learning" refers to supervised learning in general and post-Lasso (Belloni and Chernozhukov, 2013) regression with cross-validation in particular. According to Knaus (2021), the APO conditional on covariates are calculated as follows:

$$\mu_t = E\left[\mu_t(X_i) + \frac{d_i^t(Y_i - \mu_t(X_i))}{p_t(X_i)}\right] \tag{1}$$

for every t, where $d_i^t = \{D_i = t\}$ is the treatment indicator. The two nuisance parameters are the conditional expectation of the outcome $\mu_t(x) = E[Y_i|D_i = t, X_i = x]$ and the propensity score $p_t(X_i) = P[D_i = t|X_i = x]$ (Chernozhukov et al., 2018; Knaus, 2021). The variance is given by

$$\sigma^2_{\mu,t} = E\left[\left(\frac{d_i^t(Y_i - \mu_t(X_i))}{p_t(X_i)} + \mu_t(X_i) - \mu_t\right)^2\right] \tag{2}$$

The statistical inference on the average potential outcome is uniformly valid and unaffected by the post-model-selection issue. Knaus (2021) also provided formulas for calculating the pairwise ATEs by subtracting the doubly robust scores of the potential outcomes (see Eqs. (4) and (5) in Knaus (2021)).

Our controls have approximately 25 variables, and a model with second-order terms has over 200 covariates (depending on the wave). Therefore, terms with coefficients that are too small to be meaningful are possible. Hence, the Lasso procedure (Tibshirani, 1996) is used to solve the following optimization problem.

$$\min_{\beta}\left[\sum_{i=1}^{n}(Y_i - X_i\beta)^2\right] + \lambda\sum_{j=1}^{p}|\beta_j| \tag{3}$$

The Lasso functions as a variable selector by reducing the beta estimates of variables with low predictive power to zero (based on the value of λ). The post-Lasso predictions are then based on standard ordinary least squares regression with nonzero beta coefficients for a given penalty term value (selected by cross-validation). The post-Lasso regressions are then used to obtain $\mu_t(x)$ and $p_t(X_i)$ so that equations (1) and (2) can be estimated. See Knaus (2021) for more information on the methodology.

To investigate the plausible mechanism mentioned in the introduction, we perform a simple mediation analysis to investigate into the role of risk perception in mediating the relationship between perceived nonadherence and depressive symptoms. The mediation analysis is based on the following mediation model for waves 2 and 3 separately

$$risk\ perception = \alpha_1 + \beta_1 nonadherence + \beta_2 x + \varepsilon_{i1} \tag{4}$$

$$depressed = \alpha_2 + \beta_3 nonadherence + \gamma risk\ percception + \beta_2 x + \varepsilon_{i2} \tag{5}$$

For this analysis, the multivalued treatment variable is reconfigured as a dummy variable equal to 1 when noncompliance is perceived to be in the second or higher category (e.g., when about half or most people are in violation in wave 2). The product of coefficients method (MacKinnon et al., 2002) defines the mediation effect as $\beta_1\gamma$.A significant mediation effect implies that perceived noncompliance not only influences depressive symptoms directly, but also indirectly through risk perception.

Lastly, to evaluate the robustness of our result to omitted variable bias,[10] we use a method that links bias to coefficient stability (Oster, 2019). This method is based on the idea that bias arising from observed (imperfect) controls can provide information about bias arising from both observed and unobserved controls (i.e., the full set of controls). We use this approach to calculate the degree of selection on unobservables required to obtain an effect size of zero (this parameter is known as delta; see Oster (2019)). The value of this parameter indicates how much more important unobserved factors must be compared to observed factors to nullify our results.

4. Results

In our analysis, we reclassify the treatment variable in wave 2 so that "about half" and "most people" are in the same category (due to the small number of observations in the former). Wave 3 received a similar recategorization, with the "few people" and "no one" categories combined for similar reasons. Note that when we set up the analysis, we specify that main effects are not up for elimination by the Lasso algorithm, which means that the covariates shown in Tables 1A and 1B cannot be eliminated from the models; the Lasso procedure can exclude only higher-order terms. This is because the main effects include variables that are theoretically expected to be included in the analysis based on existing literature.

Figs. 1 and 2 show the (absolute) standardized difference in means

[10] We are grateful to the anonymous referees for pointing this out.

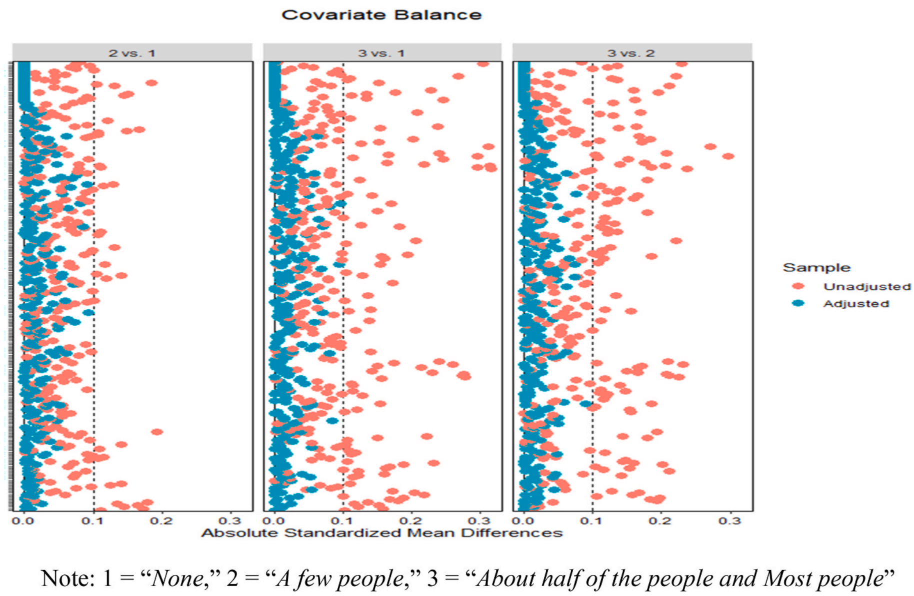

Fig. 1. Covariate balance across multivalued treatment across all covariates (Wave 2)
Note: 1 = "*None*," 2 = "*A few people*," 3 = "*About half of the people and Most people*".

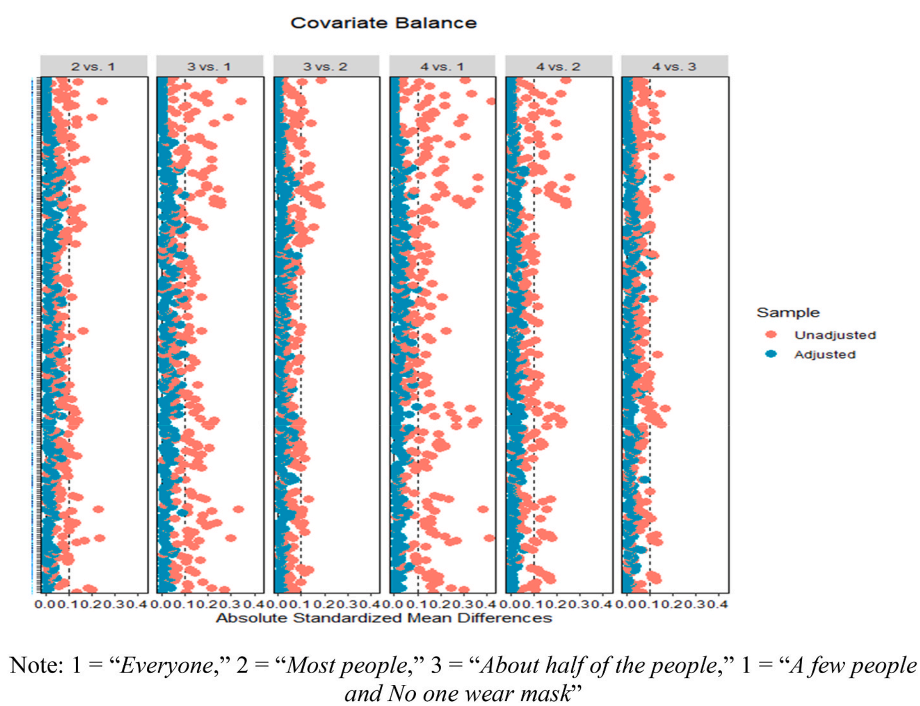

Fig. 2. Covariate balance across multivalued treatment across all covariates (Wave 3)
Note: 1 = "*Everyone*," 2 = "*Most people*," 3 = "*About half of the people*," 1 = "*A few people and No one wear mask*".

for waves 2 and 3 across the 200+ covariates (i.e., main covariates and higher-order terms). The figures depict covariate balance before (red dots) and after (blue dots) applying DML weights to the sample. The blue dots are generally closer to zero than the red dots, indicating that the DML weights reduce imbalance across the covariates. Furthermore, the weighted standardized mean differences are all less than the 0.1 threshold recommended in the literature (Austin, 2009; Stuart et al., 2013). This is significant when comparing the DML method to other matching and weighting algorithms that do not use variable selection. It is impractical in such models to consider the large number of higher-order terms that can be considered using the DML approach. The implication is that an imbalance in a higher-order term that the approach did not consider may introduce bias in the results. The DML approach effectively rules out this possibility, making the assumption of selection on observables more plausible. The DML balance the distribution of covariates even covariates that do not enter the final Lasso model, as shown in Figs. 1 and 2 (see Table 1 in the appendix for the list of variables selected by Lasso and used in the analysis).

Figs. 3 and 4 show the (average) potential outcomes for waves 2 and 3. Although the patterns are generally consistent with our main hypothesis (a positive relationship between screening positive for depressive symptoms and noncompliance with COVID-19 rules), the

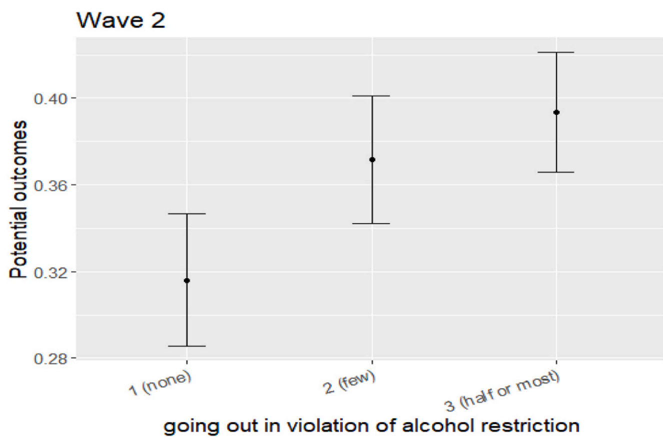

Fig. 3. Potential outcomes (Wave 2).

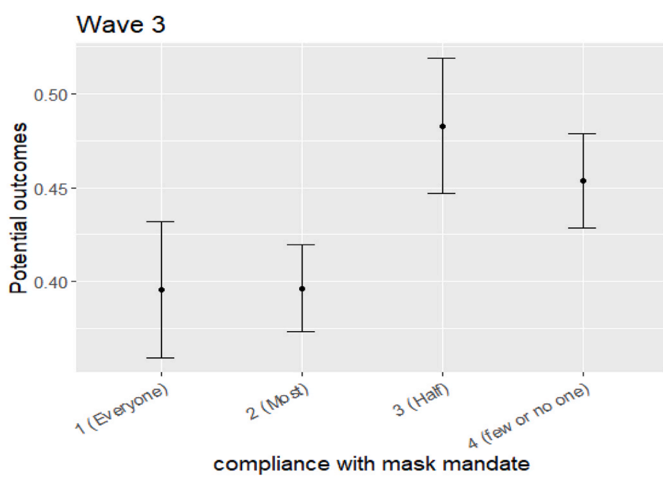

Fig. 4. Potential outcomes (Wave 3).

relationship appears to be stronger in wave 2 than in wave 3. A higher perceived level of non-adherence is associated with a higher proportion of individuals screening positive for depressive symptoms in wave 2. However, when the first two treatment levels are compared to the last two treatment levels in wave 3, the contrast is stronger, indicating a weaker relationship. Figs. 1 and 2 in the appendix show that when only the first-order terms are used to calculate balancing weights, the substantive result remains unchanged. These results are consistent with our main hypothesis.

Tables 2 and 3 show that the ATE is mostly positive and statistically significant at the 1% level, which is consistent with Figs. 3 and 4. The exceptions include when people that report "a *few people went out to drink in violation of lockdown rules*" are compared with those who report "*about half or most people are in violation*" in wave 2 (T1–T2 in Table 2), and when the first two and the last two categories are compared in wave

Table 2
Average treatment effect (ATE) for wave 2 (the outcome is patient health questionnaire (PHQ-2) (cut-off ≥2)).

	ATE	SE	t-stat	p-value
T1 - T0	0.056***	0.022	2.578	0.010
T2 - T0	0.077***	0.020	3.711	0.000
T2 - T1	0.022	0.020	1.071	0.284

T0 = "*None*," T1 = "*A few people*,"
T2 = "*About half of the people and Most people*".
***p < 0.01, **p < 0.05, *p < 0.1.
Observation on/off common support: 3220/26.

Table 3
ATE for wave 3 (the outcome is PHQ-2 (cut-off ≥2)).

	ATE	SE	t-stat	p-value
T1 - T0	0.001	0.022	0.02	0.977
T2 - T0	0.087***	0.025	3.364	0.001
T3 - T0	0.058***	0.022	2.582	0.001
T2 - T1	0.087***	0.022	3.999	0.000
T3 - T1	0.057***	0.017	3.313	0.001
T3 - T2	−0.029	0.022	−1.315	0.188

T0 "*Everyone*," T1 "*Most people*," T2 "*About half of the people*,"
T3 "*A few people and No one wear mask*".
***p < 0.01, **p < 0.05, *p < 0.1.
Observation on/off common support: 4766/236.

3 (as suggested by the graphs). Two plausible explanations exist for the stronger relationship between waves 2. First, because wave 2 was conducted much earlier in the pandemic (July/August 2020) than wave 3 (November/December 2020), the perceived threat level associated with COVID-19 may be higher in wave 2. This is most likely due to the fact that COVID-19 was relatively new earlier in the pandemic and how it is transmitted is largely unknown (Elsharkawy and Abdelaziz, 2021; Heiat et al., 2021). Therefore, the relationship between individuals' perceived risk factors and depressive symptoms may be stronger in wave 2 than in wave 3.

Second, the nature of noncompliance differs, which may impact the relationship between noncompliance and depressive symptoms. For example, South Africa was on lockdown alert level 3 when wave 2 data were collected but on alert level 1 when wave 3 data were collected. To the extent that alert levels indicate how concerned the government was about COVID-19 infections, this may translate into different attitudes and tolerances toward the population's lack of adherence.

4.1. Sensitivity analysis

When using machine learning to estimate parameters, it is critical to test the sensitivity of the estimates to parameter selection (Farrell, 2015). Specifically, are the results sensitive to the choice of the penalty term λ in the Lasso regression?

Knaus (2021) propose a data-driven approach to testing sensitivity to tuning parameter selection. The method is based on the one-standard-error rule (Breimann et al., 1984). The one-standard-error rule accounts for uncertainty in the cross-validated λ_{min} (i.e., the penalty term used in the main analysis) by moving along the penalty grid toward smaller (less complex) models.

Under DML, Knaus (2021)'s proposal complements the one-standard-error rule by considering more complex models along the penalty grid within one standard error. This method indicates whether the result is stable for various plausible penalty terms. More specifically, the approach considers more complex models along a penalty grid defined around λ_{min}, (see section 4.4 of Knaus (2021) for details). The analysis result is shown in Figs. 5 and 6 (for waves 2 and 3 respectively) and suggests that the ATE is not sensitive to parameter choice because increasing model complexity does not significantly change the estimated parameter in both waves.

4.2. Robustness to omitted variable bias

Even though we control for a large number of covariates, the selection on observables assumption remains an optimistic assumption. It is still possible that unobserved characteristics will skew our results. We employ Oster's (2019) methodology to assess the magnitude of the bias that may result from omitted variables. This method assesses how strong the selection on unobservable must be to explain our results. In this study, we regressed depressive symptoms on COVID-19 violation categories and other controls. We contrast the extremes (i.e., no violation of lockdown rules versus the highest level of violation possible, this

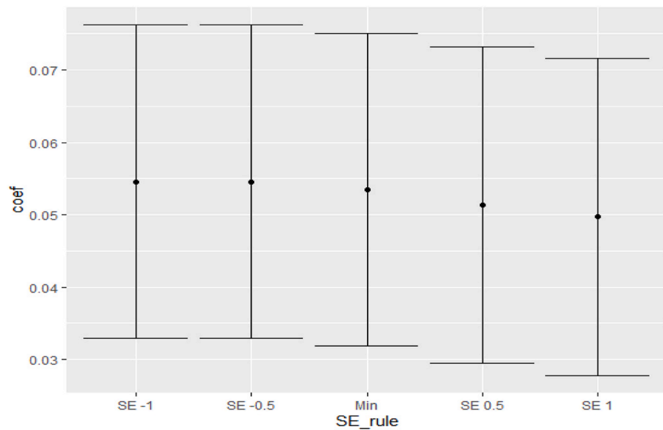

Fig. 5. Sensitivity analysis (Wave 2)
Sensitivity analysis demonstrates the estimate's resistance to small changes in the double machine learning (DML) model's parameters.

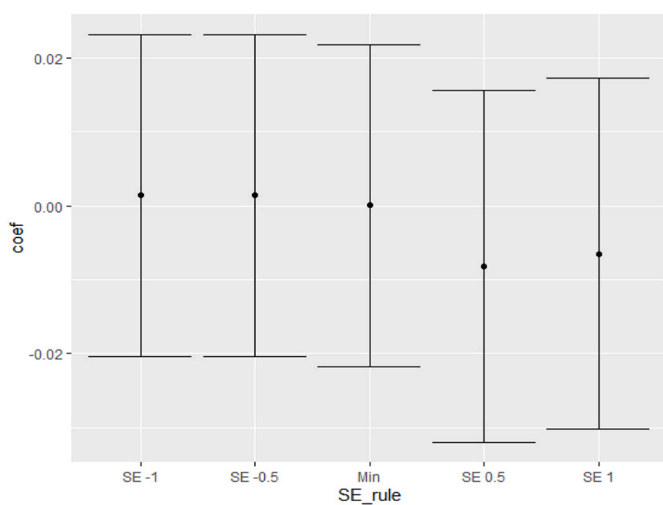

Fig. 6. Sensitivity analysis (Wave 3)
Sensitivity analysis shows the stability of the estimate to small changes in the parameters of the DML model.

corresponds to T2-T0 for wave 2 and T0-T3 for wave 3). This option allows us to concentrate on our main substantive result. The delta values for waves 2 and 3 are 2.45 and 0.19, respectively. A delta value greater than one indicates that unobserved attributes are unlikely to bias our estimate (Buggle and Nafziger, 2021). The delta estimate for wave 2 implies that unobserved factors must be 2.5 times more important than observed factors to negate our result. The implication is that, while our result in wave 2 is likely robust to unobservables, our result in wave 3 is not. Similarly, to our DML results, it appears that the relationship between perception of neighbor's behavior and depressive symptoms is more robust in wave 2. This is perhaps attributable to the reasons mentioned earlier (i.e., stringency of lockdown and knowledge about COVID-19).

5. Plausible mechanism

As mentioned in the introduction, risk perception may play a role in the relationship between perceived noncompliance and report of depressive symptoms, which we examine in this section (through shared spaces). If this is the case, then one should expect (i) a positive correlation between non-adherence and risk perception, and (ii) some of the effect of neighborhood perception of noncompliance on depressive symptoms to be through risk perception.

The full mediation analysis results (i.e., regressions corresponding to equations (3) and (4)) and a breakdown of the different effects for both waves are presented in Tables 2 and 3 in the appendix. Table 4 provides a summary of the results and standard errors.

This table depicts the effect of risk perception in mediating the relationship between observed noncompliance and depressive symptoms. The total effect is the sum of the direct and indirect effects (i.e., average conditional mediation effect (ACME)). The indirect effect is the effect that operates through risk perception (the mediation variable).

Table 4 shows a positive relationship between noncompliance and depressive symptoms, which is consistent with our DML results. Furthermore, it demonstrates that noncompliance and risk perception are positively related (irrespective of wave). Table 4 also show that at the 1% level, the total, direct, and average conditional mediation effect (ACME) are all statistically significant. A significant total effect is consistent with our DML results, and significant ACME across waves demonstrate that, in addition to the direct effect, some of the effect of noncompliance on depressive symptoms operates via risk perception. A positive ACME also indicates a positive relationship between risk perception and perceived noncompliance by neighbors. The last row of Table 4 shows that risk perception accounts for 12% and 11% of the relationship between perceived noncompliance and depressive symptoms, in waves 2 and 3 respectively.

6. Discussion and conclusion

The adverse effect of the COVID-19 pandemic on mental wellbeing is receiving more attention. The relationship can be explained through various channels, including risk perceptions of contracting the virus, social isolation, job loss, and economic insecurity. This paper investigates whether an individual's refusal to comply with COVID-19 nonpharmaceutical preventive measures harms the wellbeing of their neighbors. Our results show that those who perceive that their neighbors are not complying with COVID-19 rules are more likely to report depressive symptoms. Furthermore, we find that the level of perceived noncompliance is related to the reporting of depressive symptoms. The result suggests that this relationship is robust to unobserved factors in wave 2 (earlier on in the pandemic). The implication is that the severity of the lockdown influences the relationship between perceived noncompliance and depressive symptoms (wave 2 data were collected under lockdown level 3, whereas wave 3 data were collected under lockdown level 1). Our mediation analysis shows that risk perceptions explain at least 11% of the relationship between noncompliance and depressive symptoms.

South Africa is a fragmented society (due in part to apartheid's legacy), and spatial inequality in socioeconomic status persists. This is exemplified by the country's peri-urban settlements and densely populated townships, which are frequently poorly planned (Thani et al., 2018; Vosloo, 2020). In the context of COVID-19, this means that existing inequalities are exacerbated. Although residents of more affluent areas have an abundance of facilities, such as shopping malls, to meet people's basic needs during the hard lockdown, this is not the case in poorer areas, where the majority of the population resides. The implication is that a disparity exists in people's ability to observe social

Table 4
Mediation analysis (waves 2 and 3).

Outcome variable: PHQ-2 (cut-off $\geq$2)	wave 2		wave 3	
	Mean	SE	Mean	SE
ACME or indirect effect	0.03***	0.01	0.03***	0.01
Direct Effect	0.19***	0.06	0.23***	0.05
Total Effect	0.22***	0.06	0.26***	0.05
% of Total Effect mediated	0.12		0.11	

***p < 0.01, **p < 0.05, *p < 0.1.

distancing in these facilities (i.e., when they have to leave their homes for legitimate reasons like visiting the mall to obtain essentials). At the inception of the pandemic, visits to these essential service providers (e.g., malls and pharmacies) in poorer areas often involved long queues with little social distancing (Sewpaul et al., 2021). Reports suggest that social distancing is simply not possible in some poorer areas,[11] due to population density and lack of adequate infrastructure. In these areas, the perception that neighbors are not adhering to lockdown rules may heighten risk perception in shared spaces. This emphasizes the significance of making vaccines available as soon as possible and encouraging vaccine acceptance among the population for the sake of physical and mental health.

This result suggests that vaccine apprehension may have the same effect on psychological health in the context of workplaces or other shared spaces. A sizable proportion of the population is hesitant to receive the vaccines. Therefore, the perception that people with whom one shares a workspace are not vaccinated may harm one's wellbeing. Furthermore, according to World Health Organization (2021), "no vaccine is 100% effective, and breakthrough infections are regrettable but are to be expected." Although COVID-19 vaccine will protect against serious illness and death, it is unclear how well it will prevent infection and spread of the virus to others (World Health Organization, 2021). As a result, it is critical to continue to focus on WHO-recommended preventive measures. Despite the availability of vaccines, updated WHO recommendations continue to include hand washing and physical distancing.[12] Given our results, this may still be important for psychological wellbeing.

Therefore, our findings highlight the importance of encouraging collective compliance and adherence to regulations in the context of any easily transmitted health emergency. Research suggests that there is a positive probability of another pandemic with the size and impact of COVID-19 (Marani et al., 2021). Hence, understanding how this pandemic increases the prevalence of depressive symptoms is critical for informing policy should another pandemic occur. More broadly, our findings suggest that good health behavior is important not only for one's own physical and psychological health but also for the physical and psychological health of others. Extending the collective action argument to vaccination, this study supports arguments for mandatory vaccination on the grounds that vaccination is not intended to prevent harm to oneself alone, but also to prevent harm to others. This method will both control virus transmission and reduce the pandemic's negative mental health effect through reduced risk perception.

Finally, we should point out that this study has some limitations. There is an important caveat to keep in mind when interpreting our results. Because our measure of depressive symptoms is self-reported, there is a risk of false positive and false negative screening for depression diagnosis (Chen et al., 2022).

Ethics approval and consent to participate

Ethics approval for the NIDS-CRAM Survey was granted by the Commerce Faculty Ethics Committee of the University of Cape Town and the Research Ethics Committee: Social, Behavioral and Education Research, of the University of Stellenbosch.

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Author contribution

Adeola Oyenubi: Conceptualization, Methodology, Data curation, Formal analysis, and writing of – original draft. Uma Kollamparambil: Conceptualization, Methodology, and writing

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Data availability

Data is freely available, see the draft for details

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2023.106191.

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[11] See https://www.groundup.org.za/article/covid-19-whats-happening-townships/and https://www.theguardian.com/global-development/gallery/2020/apr/15/deep-inequalities-of-social-distancing-in-south-africa-in-pictures-coronavirus for example.

[12] See https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public.

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